Multiagent Architecture for Monitoring the North-Atlantic Carbon Dioxide Exchange Rate

Javier Bajo[1] and Juan M. Corchado[2]

[1] Universidad Pontificia de Salamanca
C/Compañía 5, 37002, Salamanca, Spain
jbajope@upsa.es
[2] Departamento Informática y Automática
Universidad de Salamanca
Plaza de la Merced s/n
37008, Salamanca, Spain
corchado@usal.es

Abstract. This paper presents an architecture that makes it possible to construct dynamic systems capable of growing in dimension and adapting its knowledge to environmental changes. An architecture must define the components of the system (agents in this case), as well as the way in which those components communicate and interact with each other in order to achieve the system's goals. The work presented here focuses on the development of an agent-based architecture, based on the use of deliberative agents, that incorporate case based reasoning. The proposed architecture requires an analysis and design methodology that facilitates the building of distributed systems using this technology. The proposal combines elements of existing methodologies such as Gaia and AUML in order to take advantage of their characteristics. Moreover the architecture takes into account the possibility of modelling problems in dynamic environments and therefore the use of autonomous models that evolve over time. To solve this problem the architecture incorporates CBR-agents whose aim is to acquire knowledge and adapt themselves to environmental changes. The architecture has been applied to model for evaluating the interaction between the atmosphere and the ocean, as well as for the planification and optimization of sea routes for vessels. The system has been tested successfully, and the results obtained are presented in this paper.

1 Introduction

An architecture must define the components of the system, as well as the way in which those components communicate and interact with each other in order to achieve the system's goals. An agent architecture should provide support for the basic properties of an agent: autonomy, communication, learning, goal orientation, mobility, persistence, etc. Autonomy, learning and reasoning are especially important aspects for an agent. These capabilities can be modelled in different ways and with different tools [22]. One of the possibilities is the use of Case

R. Marín et al. (Eds.): CAEPIA 2005, LNAI 4177, pp. 321–330, 2006.

Based Reasoning (CBR) systems. This paper presents a CBR-agent based architecture that is the core of a distributed system, principally characterized by the utilization of CBR-BDI agents [5]. These agents are capable of learning from initial knowledge. They interact with the environment and with the users within the system and adapt themselves to environmental changes. The mission of the distributed system is to monitor the interaction between the ocean surface and the atmosphere. Initially the system has been used to evaluate and predict de quantity of CO2 exchanged in the North Atlantic Ocean as well as generating optimal sea routes for vessels. The aim of this work is to obtain an architecture that makes it possible to construct dynamic systems capable of growing in dimension and adapting its knowledge to environmental changes. Several architectures have been proposed for building deliberative agents, most of them based on the BDI model. In the BDI model the internal structure of an agent and therefore its ability to choose a course of action is based on mental attitudes. The advantage of using mental attitudes in the design and realization of agents and multi-agent systems is the natural (human-like) modelling and the high abstraction level. The BDI model uses Beliefs as information attitudes, Desires as motivational attitudes and Intentions as deliberative attitudes for each agent. The method proposed in [4,10] facilitates the CBR systems incorporation as a reasoning engine in BDI agents, which makes it possible for an agent to have at its disposal a learning, adaptation and a greater degree of autonomy than a pure BDI architecture [11].

One of the greatest obstacles for the development of agent based architecture is that, we do not yet have at our disposal compliance standards or fully developed methodologies that guide us through the steps needed for optimal analysis and design. Some methodologies have been proposed such as Gaia [22], AUML [1,15,16], MAS-CommonKADS [12], MaSE [8], ZEUS [14], MESSAGE [9]. However, generally, these methodologies are incomplete or present certain restrictions. In this study the decision was made to carry out an analysis and design for our MAS using a combination of elements from the Gaia and Agent Unified Modelling Language (AUML) methodologies. Gaia is an uncomplicated methodology that allows a simple analysis and initial design, through which the problem can be studied at a general level. The advantage is that it is possible to obtain a quick, low-detailed study. On the other hand, the problem arises once the Gaia design has been completed and the level of abstraction is found to be too high. As far as AUML is concerned, the final design is sufficiently accurate for immediate implementation, but it begins the study of the problem at a level that is overly specific and detailed level. Our idea was to take advantage of both methodologies: to carry out an initial Gaia analysis and design, and subsequently, after taking into account the appropriate changes, to continue with a detailed AUML design. This makes it possible to obtain a general view of the problem in terms of organization as well as a detailed description of the MAS, greatly facilitating in the development of the project.

BDI agents can be implemented by using different tools. One very interesting tool is Jadex [17], a BDI reasoning engine that can be used on top of different middleware infrastructures such as JADE [2]. Jadex agents deal with the concepts of beliefs, goals and plans. Beliefs, goals and plans are objects that can be created and handled within the agent at execution time. A belief can be any type of java object and is stored within the beliefs base. A goal represents a motivation that has influence on agent behaviour. A plan is a java procedure and is executed in order to achieve goals. Jadex has the advantage of allowing programmers to include their own deliberative mechanisms. In our case this mechanism will be a CBR system. Moreover our system will benefit from all the communication advantages that JADE provides.

In the next section we review the relationships that can be established between CBR and BDI concepts. Section three describes the environmental problem that motivates most of this research. Section four describes the multiagent based system developed, paying special attention to the CBR-BDI agents constructed. Finally the conclusions and some preliminary results are presented.

2 CBR-BDI Agents

CBR is a paradigm based on the idea that similar problems have similar solutions, so that a new problem is solved by consulting the cases memory in search of a similar case solved in the past. The deliberative agents, proposed in the framework of this research, use this concept to gain autonomy and improve their problem solving capabilities. Figure 1 shows the activity diagram of a CBR-BDI agent for one of the possible actions, which is composed of a reasoning cycle that consists of four sequential phases: retrieve, reuse, revise and retain. An additional activity, revision of the expert's knowledge, is required because the memory can change as new cases appear during this process. Each of these activities can be automated, which implies that the whole reasoning process can be automated to a certain extent [11]. According to this, agents implemented using CBR systems could reason autonomously and therefore adapt themselves to environmental changes.

The CBR system is completely integrated into the agents' architecture. The CBR-BDI agents incorporate a 'formalism' which is easy to implement, whereby the reasoning process is based on the concept of intention. Intentions can be seen as cases, which have to be retrieved, reused, revised and retained. This makes

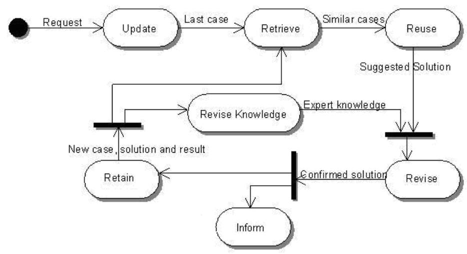

Fig. 1. Activity diagram for a CBR-BDI agent, including the reasoning cycle

the model unique in its conception and reasoning capabilities. The structure of the CBR system has been designed around the concept of a case.

The relationship between CBR systems and BDI agents can be established by implementing cases as beliefs, intentions and desires which lead to the resolution of the problem. As described in [7], in a CBR-BDI agent, each state is considered as a belief; the objective to be reached may also be a belief. The intentions are plans of actions that the agent has to carry out in order to achieve its objectives [3], so an intention is an ordered set of actions; each change from state to state is made after carrying out an action (the agent remembers the action carried out in the past when it was in a specified state, and the subsequent result obtained). A desire will be any of the final states reached in the past (if the agent has to deal with a situation, which is similar to one in the past, it will try to achieve a similar result to that previously obtained).

3 Air Sea Interaction Problem

In recent years a great interest has emerged in climactic behaviour and the impact that mankind has had on the climate. One of the most worrying factors is the quantity of CO2 present in the atmosphere. CO2 is one of gases produced by the greenhouse effect, and contributes to the fact that the Earth has a habitable temperature, provided that its quantity is limited. Without carbon dioxide, the earth would be covered in ice. On the other hand, excess CO2 blocks the heat transfer into the atmosphere, acting as an infrared radiation absorbent, preventing heat from leaving the atmosphere, therevy causing excessive warming of the planet [18]. Until only a few years ago, the photosynthesis and breathing processes in plants were considered as the regulatory system that controls the presence of CO2 in the atmosphere. However, the role played by the ocean in the regulation of carbon volume is very significant and so far remains indefinite [19]. Current technology offers the possibility of obtaining data and estimates that were beyond expectations only a few years ago. These data offer insights into the biological processes which govern the sink/source conditions for carbon dioxide [13,20]. Based on the knowledge acquired, we will be able to make predictions on the future behaviour of the atmosphere.

The goal of our project is to construct a model that calculates the global air-sea flux of CO2 exchanged between the atmosphere and the surface waters of the ocean, as well as the global budgets of CO2 for the whole oceanographic basin. In order to create a new model for the CO2 exchange between the atmosphere and the oceanic surface a number of important parameters must be taken into consideration: sea surface temperature, air temperature, sea surface salinity, atmospheric and hydrostatic pressures, the presence of nutrients and the wind speed vector (module and direction). These parameters can be obtained from oceanographic ships as well as from satellite images. Satellite information is vital for the construction of oceanographic models, and in this case, in order to produce estimates of air-sea fluxes of CO2 with much higher spatial and temporal resolution, using artificial intelligence models than can be achieved realistically by direct in situ sampling of upper ocean CO2. In order to handle all the potentially useful data to create daily models in reasonable time and at a reasonable cost, it is necessary to use automated distributed systems capable of incorporating new knowledge. Our proposal is presented in the following section.

4 Multiagent System for the Air-Sea Interaction

The option we have chosen in order to find a suitable analysis and design methodology that could be applied to our problem, was to use a mixed methodology with concepts from the Gaia [22] and AUML [1,15,16] methodologies. Our aim is to take advantage of the strengths of both concepts. The Gaia methodology is based on organizational criteria that allows a quick and effective analysis and design. The results obtained after applying Gaia consist of a high abstraction level of complexity. At that moment, the Gaia design must be adapted so that AUML techniques can be applied. Figure 2 shows the steps followed during our development process. It can be seen that Gaia is used to obtain a high level analysis and design and AUML is applied then to obtain a detailed low level design.

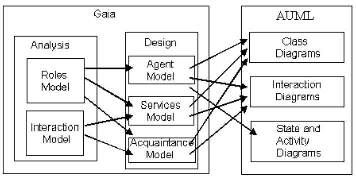

Fig. 2. Methodology used for the development process

4.1 Gaia Analysis and Design

Gaia is a methodology for agent-oriented analysis and design. The Gaia methodology is both general, in the sense that it is applicable to a wide range of multi-agent systems, and comprehensive, in the sense that it deals with both the macro-level (societal) and the micro-level (agent) aspects of systems. Gaia is founded on the view of a multi-agent system as a computational organisation consisting of various interacting roles [22]. Gaia analysis involves two models, the role model and the interaction model. Based on the requirements of the air-sea interaction problem, six roles are defined: The STORING role deals with the obtaining and storing of permanent data in the approporiate data bases. The PROCESSING role transforms the satellite images into cases. The DATACAPTURING role obtains data coming from Vessels. The CONSTRUCTAPARTIALCO2MODEL role deals with the generation of models. The OBTAINCO2EXCHANGE role calculates the CO2 exchange rate by means of the use of the models available. The AUTOEVALUATION role evaluates a model by comparing its parameters with the real data obtained through the Vessels' sensors. Finally, the PROCESSINGINFORMATION role allows a user to interact with the system. Figure 3 shows the role model for the OBTAINCO2EXCHANGE role, with a specification of its characteristic attributes such as: responsibilities, permissions, activities and protocols [22].

Role Schema: OBTAINCO$_2$EXCHANGE (OCE)

Description:
Obtains the CO_2 interchange rate from the current model.

Protocols and Activities:
CalculateExchange, SendExchange

Permisions:
Reads: Model BD

Changes: Model BD

Generates

Responsabilities:
Liveness:
OBTAINEXCHANGE:CalculateExchange.SendExchange

Safety: Succesful connection with BD established

Fig. 3. Gaia roles model for the OBTAINCO2EXCHANGE role

As far as interaction model is concerned, dependences and relationships between roles must be established. Each interaction between two roles is modelled by means of a protocol. In our MAS the following interaction protocols are required: ObtainNewModelSuper, ObtainNewModelAuto, ObtainStore, ObtainStModel, ObtainNewModelStoring, ObtainInsituData, ObtainConstructData, ObtainVessel, ObtainEvaluationSuper, ObtainEvaluationDC, Activate/ Deactivate Sensors, Delete EPROM, ChangeStore, ChangeCase, ObtainVesselData and ObtainStExchange.

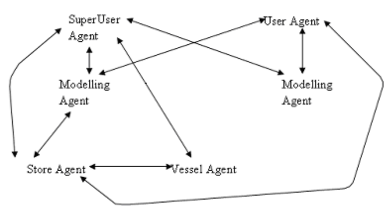

Fig. 4. Gaia acquaintance model for the air-sea interaction MAS.

As far as the Gaia design is concerned, the aim is to reduce the abstraction level so that traditional techniques can be applied. Three models are studied: agent model, service model and acquaintance model [22]. Figure 4 shows the acquaintance model for our system. Each agent communicates with the other agents. For example, the Vessel agent communicates with the SuperUser and Store agents.

4.2 Detailed AUML Design

AUML is a methodology that works at a highly detailed level, maybe too highly detailed in its initial stages if the problem we are working with is of a significant size. Our proposal deals with how to use the high level analysis and design obtained through the Gaia methodology to achieve a low level AUML design, with enough detail for an implementation to be carried out.

There are three concepts that vary slightly with respect to their meaning in Gaia and AUML: role, service and capability [1,15]. The AUML design provides class diagrams for each agent, collaboration or sequence diagrams, state and activity diagrams and protocol diagrams [1,15,16].

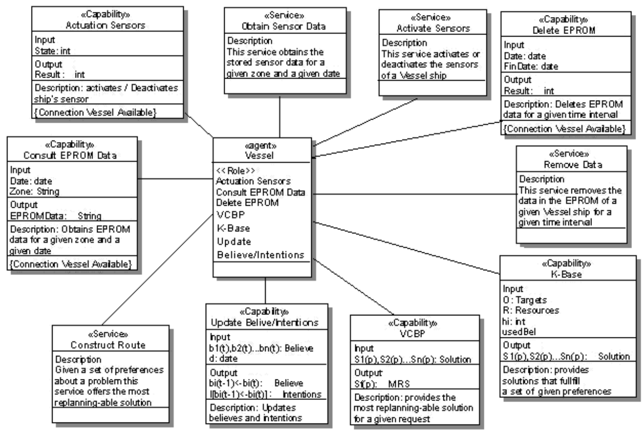

Fig. 5. Class diagram for the Vessel agent

Two CBR-BDI are used in our MAS, the Modelling agent and the Vessel agent. The first controls the generation of air-sea interaction models, as well as the management of model interaction. The second controls the management of vessels (oceanographic ships that collect insitu data required to validate the models), predominantly, the planning and optimizing of the routes taken by the vessels [10]. Figure 5 shows the class diagram for one of the two CBR-BDI agents in our system. The Vessel agent has six capabilities and offers four services to the rest of the agents in the MAS. Meanwhile, through its capabilities of Update Relieve/Intentions, K-Base and VCBP, the Vessel agent is able to carry out the stages of a CBR cycle and provide the most suitable route for a vessel based on parameters such as sea currents, obstacles, meteorological conditions, etc., when a destiny request is made. We complete the AUML design obtaining the collaboration and sequence diagrams and the protocol diagrams to represent the different interactions in the system.

Once the design is complete, the implementation can be carried out. The implementation is carried out by using the Jadex platform, which is a tool that incorporates the BDI model into the JADE agents, and the JADE platform.

The Modelling and Vessel agents are constructed with Jadex and the rest of the agents that compose the MAS are constructed with JADE. The communication mechanisms are those defined by JADE [2,17].

5 Results and Conclusions

The system described above was tested in the North Atlantic Ocean during 2004. During this period the multi-agent system has been tuned and updated and the first autonomous prototype began work in May 2004. Although the system is not fully operational and the aim of the project is to construct a research prototype and not a commercial tool, the initial results have been very successful from the technical and scientific point of view. The construction of the distributed system has been relatively simple using previously developed CBR-BDI libraries [5,6,7,10]. From the software engineering point of view AUML [1,15,16] and Gaia [22] provide an adequate framework for the analysis and design of distributed agent based systems. The formalism defined in [11] facilitates the straight mapping between the agent definition and the CBR construction. Figure 6 shows a screen shot of one of the possible views of the User agent. The user can interact with the Modelling agent (via his/her User agent) and obtain information about the carbon dioxide exchange rate of a given area.

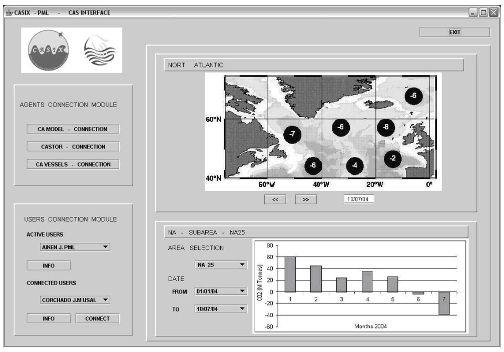

Fig. 6. Screen shot of an User agent

The fundamental concept when we work with a CBR system is the concept of case, and it is necessary to establish a case definition. A case in our problem, managed by the Modelling agent, is composed of the attributes described in Table 1. Cases can be viewed, modified and deleted manually or automatically by the agent (during its revision stage). The agent plans (intentions) can be generated using different strategies since the agent integrates different algorithms.

The interaction between the system developers and oceanographers with the multiagent system has been continuous during the construction and pruning period, from December 2003 to September 2004. The system has been tested

Table 1. Cases values

Case Field	Measurement
DATE	Date
LAT	Latitude
LONG	Longitude
SST	Temperature
S	Salinity
WS	Wind strength
WD	Wind direction
Fluo_calibrated	fluorescence calibrated with chlorophyll
SWp CO2	Surface partial pressure of CO2

Table 2. Million of tones of C02 exchanged in the North Atlanthic

	Oct. 04	Nov. 04	Dec. 04	Jan. 05	Feb. 05
Multiagent System	-18	19	31	29	28
Manual models	-20	25	40	37	32

during the last three months of 2004 and the results have been very accurate. Table 2 presents the results obtained with the Multiagent systems and with mathematical Models [13] used by oceanographers to identify the amount of CO2 exchanged. The numerical values represent the million of Tonnes of carbon dioxide that have been absorbed (negative values) or generated (positive value) by the ocean during each of the three months. The values proposed by the CBR-BDI agent are relatively similar to the ones obtained by the standard technique. In this case the case base has been constructed with over 100,000 instances, and includes data since 2002. The multiagent system has automatically incorporated over 20,000 instances during these three months and eliminated 13% of the initial ones. While the CBR-BDI Modelling Agent generates results on a daily basis without any human intervention, the Casix manual modelling techniques require the work of one researcher processing data during at least four working days. Although the system proposed requires further improvements and more work the initial results are very promising. The VCBP CBR systems embedded within the Vessel agent has provided relatively accurate results in the routes generated in the North Atlantic Waters [10]. The framework generated facilitates the incorporation of new agents using different modelling techniques and learning strategies so that further experiments will allow us to compare these initial results with the ones obtained by other techniques.

References

1. Bauer, B. and Huget, M. P. (2003) FIPA Modeling: Agent Class Diagrams.
2. Bellifime, F. Poggi, A. and Rimasa, G. (2001) JADE: a FIPA2000 compliant agent development environement. Proceedings of the 5th international conference on autonomous agents (ACM).

3. Bratman M.E., Israel D., and Pollack M.E. (1988). Plans and resource-bounded practical reasoning. Computational Intelligence, 4. pages 349-355.
4. Bratman, M.E. (1987). Intentions, Plans and Practical Reason. Harvard University Press, Cambridge, M.A.
5. Corchado J. M. and Laza R. (2003). Constructing Deliberative Agents with Case-based Reasoning Technology, International Journal of Intelligent Systems. Vol 18, No. 12, December. pp.: 1227-1241
6. Corchado J. M. and Lees B. (2001). A Hybrid Case-based Model for Forecasting. Applied Artificial Intelligence. Vol 15, no. 2, pp.105-127.
7. Corchado J. M., Pavón J., Corchado E. and Castillo L. F. (2005) Development of CBR-BDI Agents: A Tourist Guide Application. 7th European Conference on Case-based Reasoning 2004. Lecture Notes in Artificial Intelligence 3155, Springer Verlag. pp. 547-559.
8. DeLoach, S. (2001) Anlysis and Design using MaSE and AgentTool. Proceedings of the 12th Midwest Artificial Intelligence and Cognitive Science Conference (MAICS).
9. EURESCOM (2001) MESSAGE: Methodology for engineering systems of software agents. Technical report P907-TI1, EURESCOM.
10. Glez-Bedia M. and Corchado J. M. (2002) A planning strategy based on variational calculus for deliberative agents. Computing and Information Systems Journal. Vol 10, No 1, 2002. ISBN: 1352-9404, pp. 2-14.
11. Glez-Bedia M., Corchado J. M., Corchado E. S. and Fyfe C. (2002) Analytical Model for Constructing Deliberative Agents, Engineering Intelligent Systems, Vol 3: pp. 173-185.
12. Iglesias, C., Garijo, M., Gonzalez J.C. and Velasco J. R. (1998) Analysis and Design using MAS-CommonKADS. Inteligent Agents IV LNAI Volume 1365 Springer Verlag.
13. Lefevre N., Aiken J., Rutllant J., Daneri G., Lavender S. and Smyth T. (2002) Observations of pCO2 in the coastal upwelling off Chile: Sapatial and temporal extrapolation using satellite data. Journal of Geophysical research. Vol. 107, no. 0.
14. Nwana H.S., Ndumu, D. T., Lee, L. C. and Collins J. C. (1999) ZEUS: A Toolkit for Building Distributed Multi-Agent Systems. Applied Artificial Intelligence Jounal, vol 1, n^{o}13, pp. 129-185.
15. Odell, J., Levy R., and Nodine M. (2004) FIPA Modeling TC: Agent Class Superstructure Metamodel. FIPA meeting and interim work.
16. Odell, J. and Huget, M. P. (2003) FIPA Modeling: Interaction Diagrams.
17. Pokahr, A., Braubach, L. and Lamersdorf W. (2003) Jadex: Implementing a BDI-Infrastructure for JADE Agents, in: EXP - In Search of Innovation (Special Issue on JADE), Vol 3, Nr. 3, Telecom Italia Lab, Turin, Italy, September 2003, pp. 76-85.
18. Santamaría J. and Nieto J. (2000) Los agujeros del cambio climático. World Watch no. 12. pp 62-65.
19. Sarmiento J. L. and Dender M. (1994) Carbon biogeochemistry and climate change. Photosynthesis Research, Vol. 39, 209-234.
20. Takahashi T., Olafsson J., Goddard J. G., Chipman D. W. and Sutherland S. C. (1993) Seasonal Variation of CO2 and nutrients in the High-latitude surface oceans: a comparative study. Global biochemical Cycles. Vol. 7, no. 4. pp 843-878.
21. Wooldridge, M. and Jennings, N. R. (1995) Agent Theories, Architectures, and Languages: a Survey. In: Wooldridge and Jennings, editors, Intelligent Agents, Springer-Verlag, pp. 1-22.
22. Wooldridge, M. and Jennings, N. R. and Kinny, D. (2000) The Gaia Methodology for Agent-Oriented Analysis and Design. Journal of Autonomous Agents and Multi-Agent Systems, 3 (3). pp. 285-312.